Joint CSCE Construction Specialty & CRC Conference 2025
Conférence conjointe spécialisée en construction de la SCGC et CRC-2025

Montreal, Quebec
July 28-31, 2025 / *28-31 juillet 2025*

A Review of Artificial Intelligence Applications in Utility Investigation for Highway Projects

H.S. Ghali[1] and J.S. Shane[1]

[1] Department of Civil, Construction & Environmental Engineering, Iowa State University, Iowa, USA

ABSTRACT: Utility investigation is an essential activity in highway projects to designate and map existing utilities in a project and prevent any project delays caused by utility-related issues such as utility strikes. Various approaches exist for utility investigation, including the one-call system, private locators, and Subsurface Utility Engineering (SUE) or a combination of these approaches. However, these approaches are often time-consuming and labour-intensive and involve a mix of site activities, such as field visits and data collection using surveying equipment or geophysical methods, and office activities, such as utility record collection, utility record analysis and data interpretation. With the advances in artificial intelligence (AI), it is important to investigate the potential benefit this field holds to utility investigation. Accordingly, this paper provides a literature review of AI research areas relevant to utility investigation and highlights the potential benefit of these areas in addressing the existing challenges and enhancing the effectiveness of the utility investigation process. The paper focuses on three key AI areas: object detection of visible utility features, automatic generation of utility maps, automated interpretation of geophysical equipment results. Furthermore, this paper explores the potential integration of these three research areas into utility investigation and highlights their benefits in improving efficiency and accuracy in this field.

1. INTRODUCTION

The underground positioning of utilities offers significant benefits in maintaining the aesthetic appeal of communities. However, if the locations of these underground utilities are not accurately recorded, they pose a substantial risk to public safety and infrastructure. In the United States, utility strikes remain a recurrent issue, with 211,887 total damages reported in 2023, of which 47% involved telecommunication and CATV lines, while 40% affected natural gas lines (Common Ground Alliance, 2023). These incidents highlight the primary causes of utility strikes, often attributed to inaccurate or outdated utility records (Al-Bayati & Panzer, 2020; Li & Cai, 2015; Anspach & Ramsey, 2017). Accordingly, utility investigation is a critical component in any highway project to ensure that underground utilities are accurately located and mapped prior to commencing the excavation activities. The commonly known utility investigation methods are subsurface utility engineering (SUE) or private-locating services, both of which involve the use of the one-call system, a legally mandated damage prevention law by each state as one step in the process.

The utilization of these services requires carrying out a certain level of effort of utility investigation to attain the desired deliverable. To outline these efforts, the authors will focus on SUE services since it has a standardized procedure demonstrated in the ASCE 38-22 (ASCE, 2022). SUE relies on a standardized quality level (QL) framework, which includes QLD, QLC, QLB, and QLA. Table 1 summarizes some of the levels of effort for each QL; however, this is not a comprehensive list. As defined by the ASCE 38-22, QL represents a value of judgment on the reliability of the available data; therefore, assigning a QL value to the utility information requires the involvement of professionals.

Table 1: Quality Levels and Part of the Associated Tasks (Adopted from ASCE, 2022)

Quality Level	Purpose	Some of the Performed Tasks
QLD	Collecting and reviewing existing utility records.	**Collect utility records** from various sources, such as as-builts, GIS databases, service records, incident reports, utility data repositories, or others.
		Review and analyse the utility records to identify the need for further information or verification
QLC	Confirming the horizontal positioning of utility features or segments.	**Perform activities required for QLD**
		Carry out field visits to search and survey the visible utility features with 0.2 ft horizontal accuracy.
QLB	Designating the horizontal positioning of the existing utility segments	**Perform the tasks of QLC & QLD**
		Perform the appropriate geophysical method to designate the existing utilities within project limits.
		Interpret the geophysical method results in context with all the available records and information.
QLA	Locating the existing utilities	**Perform the tasks of QLB, QLC & QLD**
		Select and perform the appropriate non-destructive method to create a test hole for measuring and documenting utility segment attributes

From Table 1, it is evident that SUE is a time-consuming and labour-intensive process that requires extensive data collection of utility records, field visits to survey visible features or designate the existing utilities using geophysical methods, data interpretation of the collected results, and expert judgment to achieve accurate utility mapping. These challenges highlight the potential of using advanced technologies that can enhance and automate repetitive tasks to optimize resource allocation and increase the effectiveness of the utility investigation process. For example, the integration of AI tools by utility owners, using drones and object detection deep learning models, has reduced the manual effort required to manually inspect damaged utility poles by 60%, which allowed for faster adaptation of maintenance strategies (Cognizant, 2019). Additionally, 4M Analytics reported that their AI-enhanced utility maps can be delivered within 1-2 business days, compared to the weeks or even months typically required to generate a utility map for the existing utilities within the project limit (Garafola, 2025). Therefore, this paper aims to conduct a literature review on AI and automation research areas that can benefit utility investigation and highlight their potential applicability in the field.

2. ARTIFICIAL INTELLIGENCE AND RELEVANCE TO UTILITY INVESTIGATION

The purpose of AI is to develop machines or algorithms that can think and reason like humans and make decisions to act rationally and humanly (Russell and Norvig, 2010). Since most tasks require human involvement, AI's applicability can extend to various domains, including utility investigation. Its ability to process large datasets, identify patterns, and automate tasks makes it a valuable tool worth exploring in this field.

One of the primary research areas where AI can contribute to utility investigation is object detection which is fundamentally based on deep learning models. Object detection is specially designed to detect the presence of objects in an image by learning patterns from vast amounts of labelled training data. Similarly, object detection models can be leveraged in utility investigation to detect visible utility features such as manholes, fire hydrants, and utility poles from aerial imagery or Google street-view images. These models can automatically detect and map the visible utility features when combined with geolocation data. Additionally, geophysical equipment is used in utility investigation to obtain QLB information; the image-based results from this equipment can be analyzed using deep learning models to interpret the underground utility attributes. While automation is not necessarily AI, as it does not involve an algorithm that learns to make decisions, it is worth mentioning that this area also has potential applicability to utility investigation as it can automatically generate utility maps by fusing the available data on the existing utilities using stochastic approaches. Therefore, the following three key areas hold potential benefits to the utility investigation field: object detection and locating of utility features, automated utility mapping, and automatic geophysical results interpretation.

2.1 Object Detection and Locating of Utility Features

Detecting and locating visible utility features is essential for determining the reliability of the utility records collected from different utility owners (ASCE, 2022). Many researchers explore developing deep-learning models to detect visible utility features such as fire hydrants, manhole covers, and utility poles. A key prerequisite for training these models is the availability of a well-structured dataset of utility feature images. These images can be captured using various sources, which fall into two categories: (1) weather-dependent imagery, such as photos taken with smartphones or Unmanned Aerial Vehicles (UAV), and (2) weather-independent imagery, such as images extracted from Google Street View.

Several studies leverage weather-dependent imagery for utility feature detection, which helps in having high-resolution images. For instance, Tian et al. (2023) developed a four-step module framework for detecting and automatically reconstructing a 3D point cloud of fire hydrants using a vehicle-mounted camera to capture a video from a street-view perspective in West Lafayette, Indiana, USA. Fire hydrant images were extracted from the recorded video to train a You Only Look Once (YOLO) V5 object detection model, while PIX4D was used to generate a 3D point cloud model. This study has several limitations, including the lack of variance in fire hydrant shape and colour. Additionally, the images were captured from a street-view perspective on a single day without accounting for different weather conditions and brightness levels. Accordingly, these limitations may limit the model’s detection accuracy and applicability.

Some researchers overcome the above-mentioned limitations in their work when developing the model’s dataset. This is seen in the work of Pang et al. (2023), who enhanced the YOLOv5s model to detect road manhole covers under various maintenance conditions. The dataset was collected from a campus road in Haihe Education Park, Tianjin, China, using a mobile robot with a mounted stereo camera, and the developed model achieved a mean average precision with an intersection of union of 0.5 (mAP@0.5) of 97.9% for detecting well-maintained manholes and 95.3% for poorly maintained ones. Zhou et al. (2022) also developed a smartphone-based method for detecting and classifying road manhole covers under different maintenance and weather conditions. The study employed hierarchical Convolutional Neural Networks (CNN) for manhole detection, and the trained model is able to identify the weather condition as being rainy or not rainy and classify the manhole cover maintenance levels (good, average, poor) based on collected inertial sensor data by the smartphone. The model, trained on 12,853 images from Shenzhen University, achieved an Average Precision (AP) accuracy of 83%. Additionally, Wang and Huang (2024) employed a UAV-based method for detecting and classifying the type of manhole covers under different brightness conditions. The study employed YOLOv8 for manhole and text detection, followed by SAGAN for enhancing low-resolution text images, and VGG16-BN model for classifying manhole covers as water or sewer lines. The model is trained on 5,122 UAV-captured images and employs different data augmentation techniques to simulate the different brightness conditions and increase the model’s robustness. The model demonstrated a high detection accuracy of 97.41% for manhole detection, 98.54% for text detection, and 97.62% for text classification. Similarly, another work focused on detecting utility power poles under different brightness and occlusion conditions and utilized an improved version of the YOLOv5s model, YOLO5s-Pole, when developing the object detection model (Zhang et al., 2023). The dataset, containing 305 images, was collected from Cuitian Orange Orchard in Sihui City, Guangdong Province, using aerial UAV imagery. The model was trained on three different brightness conditions, dark, medium, and light, and the highest performance was attained in the bright conditions achieving an accuracy of 0.803. These studies demonstrate the importance of incorporating different maintenance conditions of the utility feature and different weather, brightness, and occlusion levels when developing the dataset to improve the generalizability of the AI-based utility feature detection model.

Besides detecting utility features, other studies aim to locate the utility features either using GPS receivers or LiDAR scanners. Oulahyane and Kodad (2024) developed a YOLOv8-based object detection model of manhole covers using aerial images collected from drones equipment with high-resolution cameras and GPS receivers to capture urban images of manholes in Oujda, Morocco. The model successfully detected the manhole with a mAP @0.5 of 87.74%, and the precise geo-coordinates of each detected manhole were stored in a database. Another study that combines both detecting and locating is seen in the work of Timofte and Gool (2011). The authors developed a novel multi-step pipeline that detects, recognises, and maps manhole covers in 3D using images captured by a GeoAutomation van equipped with GPS and multiple cameras. Instead of using object detection models, the study employed feature-based methods, and the experiment was conducted using high-resolution images collected from Flemish towns to validate the proposed pipeline. The findings showed that 93% accuracy is attainable when having at least four different 2D views per manhole. Other researchers utilized LiDAR when developing the dataset. For example, Yu et al. (2015) utilized a mobile laser scanner (MLS) system to develop a 3D point cloud of urban road manhole covers in Xiamen, China. The authors utilized a curb-based road surface segmentation approach, converted the 3D point cloud data to 2D intensity georeferenced images, and trained two deep learning models to detect the manhole covers. The model was trained and validated using three real-world urban datasets and achieved a precision of 0.959. Additionally, Wei et al. (2019) proposed a fully automated system to detect, locate and assess the manhole covers on urban roads in Beijing, China. The authors utilized the SSW-D Mobile LiDAR system to capture laser point cloud data and employed various algorithms for feature extraction, classification and outline detection of the manholes, including SVM and Graph-based segmentation. The trained model achieved a detection accuracy of 0.9618 for the manhole cover.

In addition to the above, another effort that combines both utility detection and mapping utility features while considering different types of utilities and various occlusion conditions is seen in the work developed by Gomes et al. (2020). The authors focused on developing an automated approach to detect and map utility poles using aerial orthoimages and the Adaptive Training Sample selection (ATSS) deep learning method. The objective is to improve the accuracy and efficiency of utility pole detection and mapping, considering various shapes and types of poles such as light poles, low-voltage electric poles, high-voltage power poles, and others. The study was conducted in Camo Grande, Brazil, using aerial RGB orthoimages provided by the city hall, and the dataset was manually labelled for training and evaluation. The results demonstrated that the ATSS outperformed the other models, achieving an average precision (AP) of intersection over union of 50 (AP@0.5) of 91.3%. The novelty of this research lies in the application of the model to detect and locate small objects in aerial orthoimages and automatic locating of these utility poles.

(a) manhole cover (b) manhole cover (c) manhole cover (d) utility pole

Figure 1: Different Objection Detection Application of Visible Utility Features, (a) extracted from Wang and Huang (2024), (b) extracted from Wang and Huang (2024), (c) extracted from Oulahyane and Kodad, (2024), (d) extracted from Gomes et al. (2020)

Based on the above research, various studies have focused on detecting or both detecting and locating utility features such as manholes, fire hydrants and utility poles using various deep-learning models, as shown in Figure 1. The datasets used for training these models can be collected using different tools, ranging from complex equipment such as Geoautomation vans equipment with GPS receivers and UAVs (Timofte & Gool, 2011; Gomes et al., 2020; Wang & Huang, 2024) to more accessible devices like smartphones (Tian et al., 2023; Zhou et al., 2022). However, the effectiveness of these datasets depends on accounting for environmental factors such as weather conditions and occlusions. Table 2 summarizes the different factors considered when developing the object detection model. To enhance model generalizability and robustness, researchers either carefully selected image collection conditions (Timofte & Gool, 2011; Gomes et al., 2020; Zhou et al., 2022) or applied data augmentation techniques to simulate different weather conditions (Wang & Huang, 2024).

Table 2: Summary of Studies on Utility Feature Detection Using Different Imagery Tools

Imagery Category	Reference	Type of Utility Detected	Locate (Y/N)	Brightness Condition (Y/N)	Maintenance Condition (Y/N)	Different Utility Type (Y/N)
Weather-Dependent imagery Method	Tian et al. (2023)	fire hydrant	N	N	N	N
	Pang et al. (2023)	manhole cover	N	N	Y	N
	Zhou et al. (2022)	manhole cover	N	Y	Y	N
	Zhang et al. (2023)	power poles	N	Y	N	N
	Wang & Huang (2024)	manhole cover	N	Y	Y	Y
	Oulahyane & Kodad (2024)	manhole cover	Y	N	Y	N
	Timofte & Gool (2011)	manhole cover	Y	Y	Y	N
	Gomes et al. (2020),	utility poles	Y	Y	Y	Y
	Yu et al., (2015)	manhole cover	Y	N	N	Y
	Wei et al. (2019)	manhole cover	Y	N	Y	Y
Weather Independent Imagery	Aydın & Erdoğan (2024)	manhole and drainage cover	N	N/A	Y	Y
	Vishnani et al. (2020)	manhole	Y	N/A	N	N

To mitigate the above-mentioned challenges, some researchers utilized Google Street View when collecting the dataset and developing the model. For instance, Aydın and Erdoğan (2024) utilized YOLOv11 to automatically detect manhole covers and drainages in images from Google Street View in Turkey. The dataset contained 635 images for manhole covers and 366 for the drainage systems and it was expanded to 1,646 images using augmentation techniques. The trained model achieved a mAp @0.5 of 0.606 when detecting the manhole covers. Besides utility features detection, other researchers presented an easily implemented methodology for detecting and mapping manholes using Google Street View imagery and image processing techniques (Vishnani et al., 2020). The model utilized canny edge detection for edge extraction and the Haversine formula for GPS coordinate computation. The dataset developed captured three different viewpoints of each manhole from Google Street View imagery, and the model achieved an accuracy of 80% in detecting and locating manholes. These approaches aim to reduce reliance on manual surveys and can assist in developing a database for existing manholes with their locations.

2.2 Automatic Utility Mapping

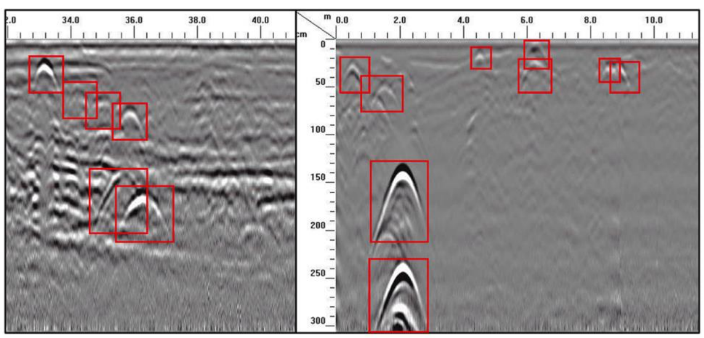
Besides detecting and locating visible utility features, these features serve as reference points for the underground utility segments (ASCE, 2022; Wang & Huang, 2024). Therefore, another perspective that researchers explored is the prediction of underground utility segments using the identified visible features or utility specifications to generate utility maps automatically. Different data sources are used when generating utility maps; some researchers relied on analysing the utility specification to determine the depth of the utility segment that it should be located at to comply with the specification. Li and Cai (2015) adopted this perspective and proposed a framework that integrates natural language processing (NLP) and spatial reasoning to infer the vertical location of underground utilities and automate compliance checking utility specifications. The NLP module extracts spatial rules from utility codes, industry standards, and government regulations and converts them into a format to be easily processed by the computer. The spatial reasoning module models the spatial relationship using topological, directional and proximity relations derived from the NLP module that enable the automatic estimation of utility depth. The effectiveness of this framework lies in its ability to check whether the constructed utility complies with the utility specification and predicts the depth of the utility segment provided they follow the required specifications. However, this is not always the case due to unforeseen conflicts or conditions faced when installing the utility lines during construction phase.

Other researchers aim to generate a utility map based on the surveyed utility features available in as-built utility records given some predetermined rules collected from experts or industry standards. For instance, Oguntoye et al. (2024) generate a probability-infused utility map by infusing the existing utility maps (from as-built or as-planned drawings) with an AI-generated utility map. The AI-generated map is created by manually surveying the visible utility features in the study area and then predicting the underground utility segments using preset rules derived from expert knowledge. The fusion process is performed using a normal probability distribution, where the AI-generated map and the as-built data are overlaid to create a final probabilistic map. This probabilistic map highlights areas with high confidence levels, where both maps align well, and areas with low confidence levels, indicating locations with high uncertainty in data. Another study introduces a novel methodology for mapping wastewater networks using georeferenced manhole cover locations as primary data points (Chahinian et al., 2019). The proposed methodology involves developing an optimization algorithm that treats manhole covers as network nodes and automatically connects them using a cost-minimization function. This function considers distance and slope constraints that comply with the industry guidelines for wastewater network design. The algorithm was validated in two towns in France where real-world wastewater network data were available. The algorithm demonstrated high accuracy in reconstructing the network topology, achieving a completeness score of 92% and correctness of 92% with an overall quality score of 85%. Additionally, the developed probabilistic network layouts highlight areas with high uncertainty which helps indicate the locations where additional field validation is required. These results showcase how AI and probabilistic modelling can identify the areas of data uncertainty within a project, helping to allocate utility investigation efforts more effectively. Accordingly, it reduces unnecessary utility investigation and optimises resource allocation.

2.3 Automatic Geophysical Results Interpretation

When field validation is needed in areas of uncertainty within collected utility records, geophysical equipment is commonly used to locate the underground utility segments horizontally, gather additional data attributes and identify abandoned utility lines that do not appear in utility records. The commonly used geophysical equipment is the Ground Penetrating Radar (GPR), which generates B-scan 2D images that capture variations in electromagnetic wave signals as they are transmitted into the ground and reflected back to the receiver (Su et al., 2023). However, interpreting GPR results is time-consuming and requires expert knowledge in geophysics to differentiate between the subsurface utilities signal and soil layers and confirm the environmental inference that may affect the GPR results. Accordingly, researchers explored the possibility of training a deep learning model to learn the pattern within GPR images and automate the result interpretation process. A study proposed a novel deep learning approach to automate the analysis of GPR data to allow for the automatic horizontal and vertical localization of underground utility pipes while reducing the time and cost associated with manual interpretation (Yamaguchi et al., 2021). The research integrated a 3D Convolutional Neural Network (3D-CNN) for feature extraction, especially detecting parabolic patterns of GPR scan images and Kirchoff migration for precise vertical positioning of detected pipe. The dataset was developed from GPR scanning of 230 km of GPR scans at a scanning speed of up to 80 km/h and then manually labelling it to indicate the pipe direction (transverse or longitudinal). The developed model is able to interpret the 3D positions and orientation of pipes with a positional error to within 20 cm. Another research by Su et al. (2023) proposed an end-to-end underground utility localization (EUUL) model that automates the localization of underground utilities (UUs) using GPR B-scan images, as shown in Figure 2. The dataset consisted of real B-scan images collected from 8 km of GPR data in Jiangsu Province, China, which involved environmental interference and the two distinct types of geological conditions: (1) soil containing gravel and rock and (2) clear soil with a high density of underground utilities. The results demonstrated that the EUUL model outperformed the traditional object detection models, such as Faster R-CNN and YOLOv3, achieving a locational accuracy of 97.01%.

Other research work aims to integrate the interpretation of GPR B-scan images and the automatic generation of 3D models; this can be seen in the framework developed by Feng et al. (2021). The authors introduced a novel deep learning-based system to automate the detection, positioning, and 3D reconstruction of underground utilities using GPR B-scan images; the research methodology involves using an omnidirectional robotic system equipped with a GPR antenna to automatically collect georeferenced GPR data and restrict any rotation to improve the positional accuracy. The collected GRP B-scan images are then processed using a deep neural network (DNN) migration module that translates the raw GPR scans into cross-sectional images of underground utilities. Then, the GPRNet model is used to reconstruct a 3D point cloud from the cross-section images generated by DNN. This approach was tested using simulated datasets and real-world field tests in River Edge, New Jersey. The novelty of this research lies in the integration between GPR data collection and the 3D reconstruction of detected underground utilities.



Area 1 (complex soil type with large pieces of gravel and holes) **Area2** (simple soil type with congested pipelines)

Figure 2: Automatic Detection of Parabola in GPR B-Scan Results (Su et al., 2023)

3. POTENTIAL UTILIZATION OF AI IN THE UTILITY INVESTIGATION FIELD

Based on the above-mentioned research in the AI and automation field, the developed applications relevant to utility investigation remain fragmented, and there are limited studies that demonstrate how these tools can be holistically integrated into a unified process in the utility investigation field. While individual use cases, such as object detection, automatic utility mapping and geophysical data interpretation, have been explored in the literature to serve other fields such as asset inspection and maintenance and automatic generation of utility maps, there is a lack of a conceptual approach that illustrates how these technologies can also serve the utility investigation process. Therefore, the purpose of this section is to present a conceptual, high-level approach that visualizes the potential integration of these distinct AI and automation applications to support the utility investigation process. Moreover, the use of these AI and automation tools is intended to serve as a complementary means for extracting data about the existing utilities and does not replace the formal procedures outlined in the ASCE 38-22 to achieve the required quality level.

Initially, one of the primary tasks in the utility investigation, particularly when working towards achieving QLD and QLC, is collecting utility records and conducting site visits to verify the accuracy of the collected records and the presence of the utility features in the field, as highlighted in Table 1. One of the tools that can serve as an additional data source for collecting information on visible utility features is the object detection model. Instead of relying solely on utility records to identify these features, data collection sources such as aerial imagery, smartphone cameras, or Google Street View, integrated with GPS receivers, can be utilized to capture images of the existing utility features. Then, these images can be inputted into an object detection model to detect the visible utility features and determine the geolocation coordinates of these features. These models facilitate the mapping of visible utility features onto the collected utility records to assess the accuracy and determine whether they are updated or not. Furthermore, the detected and georeferenced utility features can be stored in a database that functions as a utility asset management system. This allows for the reuse and continuous updating of this database and can be used as a validation tool to determine the accuracy of the utility records collected from utility owners.

After detecting and locating the utility features using the object detection models, the detected and located utility features can be inputted to the automatic utility mapping tool. This tool integrates detected and located utility features with predefined rules, developed based on expert knowledge, in the utility field to generate an AI utility map (Oguntoye et al., 2024; Chahinian et al., 2019). This generated AI utility map can be compared with the collected utility records to identify areas with low confidence levels, indicating a need for further field investigation. Traditionally, this comparison is done manually and is a time-consuming process; however, as illustrated by Oguntoye et al. (2024), this comparison can be automated, which results in the generation of a probabilistic utility map. This automatic comparison significantly reduces the time and resources required for utility records analysis. It also helps identify areas within the project limits where discrepancies between different data sources occur, i.e. areas with low confidence levels, which in turn assists in prioritising locations that require further field investigation using geophysical methods. This enables more efficient resource allocation in the field investigation, ensuring efforts are focused on regions with high uncertainty and reducing the number of field visits carried out which will lead to lower fuel consumption and reduced emissions.

After identifying the project areas requiring further field investigation using geophysical methods and conducting this investigation using GPR, the results of the GPR require analysis and expert knowledge in geophysics and is a timing consuming task. Therefore, the deep-learning models developed to analyze the GPR results automatically can be utilized to predict the horizontal and vertical location of the existing utilities. This tool can assist the experts in analysing the GPR results, thus saving time in this task that is performed to reach QLB, as highlighted in Table 1. After designating the uncertain project areas and automatically interpreting the horizontal and vertical location of the existing utilities, this information can be used to update the probabilistic utility map to have a utility map with high certainty. Figure 3 shows a summary of the integration of AI in the utility Investigation field.

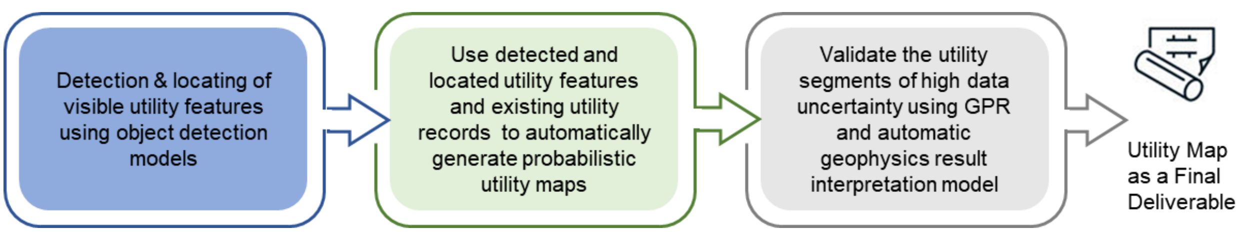


Figure 3: Potential Integration of AI in the Utility Investigation Field

4. CONCLUSION

Utility investigation is imperative on every highway project to accurately identify and locate the underground utilities before excavation to prevent utility strikes. The challenges faced in this field lie in the inaccurate utility records received from utility owners and the intense efforts and time required to verify these records to output a utility map of the existing utilities in the project limit. Therefore, this paper explored the research work in the artificial intelligence field that is relevant to the utility investigation and holds potential benefits to this field. The paper highlighted three relevant key areas: object detection models, automated utility mapping tools, and automatic interpretation of geophysical results using deep-learning models. The authors highlight the potential benefit of each research area and mention the benefit of integrating these three areas to generate utility maps that can serve as an additional utility information source when determining the validity of the collected utility records from utility owners.

While this review highlights the applications of AI in utility investigation, several practical challenges exist when implementing it in the real world. Most of the developed models are trained on datasets tailored to specific utility features, such as manholes, fire hydrants, or utility poles, and specific localized conditions, including specific shapes, brightness levels, and weather conditions, as shown in Table 2. As a result, these models are often limited in their application and can not be generalized beyond the specific conditions for which they were trained. To implement these technologies in practice, organisations would either need to access a pre-trained model and evaluate its performance on their specific utility feature or develop new, customized datasets and train a deep learning model accordingly. In both cases, a significant initial investment is typically required (Abioye et al., 2021). This includes costs related to developing the dataset required to train the model, purchasing the required computation power for training the models, employing the required AI engineers to develop this system, pilot testing, staff training and establishing new workflows and procedures to allow for the integration of this new technology into the organization's existing workflow. Additionally, the construction industry also faces cultural challenges. These include the slow adaptation of new technologies in the industry and the lack of trust in AI technology, which may further slow down its adoption (Abioye et al., 2021). Therefore, these barriers represent significant considerations for organizations to consider when adopting AI for utility investigation.

For future research, further studies are needed to assess the practical implementation and industry adoption of AI in utility investigation, including its cost-effectiveness, reliability and integration into existing workflow. Additionally, researchers can explore the alignment between QL stipulated in ASCE 38-22 and AI-generated outputs, such as detected utility features and probability utility maps and evaluate the QL assigned to the deliverables of the AI-based methods.

REFERENCES

Abioye, S. O., Oyedele, L. O., Akanbi, L., Ajayi, A., Delgado, J. M. D., Bilal, M., Akinade, O. O., & Ahmed, A. (2021). Artificial Intelligence in the construction industry: a review of present status, opportunities and future challenges. *Journal of Building Engineering*, *44*(1), 103299. Sciencedirect. https://doi.org/10.1016/j.jobe.2021.103299

Al-Bayati, A. J., & Panzer, L. (2020). Reducing damages to underground utilities: Importance of stakeholders' behaviors. Journal of Construction Engineering and Management, 146(9), 04020107. https://doi.org/10.1061/(asce)co.1943-7862.0001899

Anspach, J. H., & Ramsey, R. E. (2017). Optimizing utility investigations on large Design-Build projects. Pipelines 2017, 148–159. https://doi.org/10.1061/9780784480885.015

ASCE (American Society of Civil Engineers). (2022). Standard guideline for investigating and documenting existing utilities (38-22). Asce.org. https://sp360.asce.org/personifyebusiness/Merchandise/Product-Details/productId/280994734

Aydın, C., & Erdoğan, G. (2024). Artificial Intelligence supported city infrastructure management: automatic detection of manholes covers and drainage with YOLO on Google Street View images. Journal of Business in the Digital Age, 112–124. https://doi.org/10.46238/jobda.1575356

Chahinian, N., Delenne, C., Commandré, B., Derras, M., Deruelle, L., & Bailly, J.-S. (2019). Automatic mapping of urban wastewater networks based on manhole cover locations. Computers, Environment and Urban Systems, 78, 101370. https://doi.org/10.1016/j.compenvurbsys.2019.101370

Cognizant. (2019). *Case Study: Energy & Utilities - AI Analytics and Drones Cut Utility Costs to Boost Reliability*. Www.cognizant.com. https://www.cognizant.com/en_us/case-studies/documents/ai-analytics-and-drones-cut-utility-costs-boost-service-reliability-codex4357.pdf

Common Ground Alliance. (2023). DIRT 2023 analysis and recomendations. In DIRT Report. https://commongroundalliance.com/Portals/0/Common-Ground-Alliance-DIRT-Report-2023-FINAL.pdf

Feng, J., Yang, L., Hoxha, E., Sanakov, D., Sotnikov, S., & Xiao, J. (2021). GPR-based model reconstruction system for underground utilities using GPRNet. ArXiv (Cornell University). https://doi.org/10.1109/icra48506.2021.9561355

Garafola, C. (2025). *The Future of Utility Mapping, AI Innovations, and Winning with 4M*. 4manalytics.com; 4MAnalytics. https://www.4manalytics.com/blog/4m-vision-2025-product-roadmap

Gomes, M., Silva, J., Gonçalves, D., Zamboni, P., Perez, J., Batista, E., Ramos, A., Osco, L., Matsubara, E., Li, J., Marcato Junior, J., & Gonçalves, W. (2020). Mapping utility poles in aerial orthoimages using ATSS deep learning method. Sensors, 20(21), 6070. https://doi.org/10.3390/s20216070

Landin, W., Cowden, J., Griffitt, M., Dempsey, A. D., & Easton, F. (2016). Integration of utility locations, surveying, and ROW mapping to support the planning-level design of over 200 miles of pipeline. Pipelines 2017. https://doi.org/10.1061/9780784479957.081

Li, S., & Cai, H. (2015). Automated underground utility mapping and compliance checking using NLP-Aided spatial reasoning. Computing in Civil Engineering, 419–426. https://doi.org/10.1061/9780784479247.052

Li, X., & Jiang , H. (2017). Artificial Intelligence technology and engineering applications. The Applied Computational Electromagnetics Society Journal (ACES), 32(5), 381–388.

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (1955). A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence, August 31, 1955. AI Magazine, 27(4), 12–12. https://doi.org/10.1609/aimag.v27i4.1904

Oguntoye, K. S., Laflamme, S., Sturgill, R., Salazar, D. A., Eisenmann, D. J., & Kimber, A. (2024). Probabilistic method to fuse artificial intelligence-generated underground utility mapping. Sensors, 24(11), 3559–3559. https://doi.org/10.3390/s24113559

Oulahyane, A., & Kodad, M. (2024). Advancing urban infrastructure safety: modern research in deep learning for manhole situation supervision through drone imaging and geographic information system integration. International Journal of Advanced Computer Science and Applications, 15(7). https://doi.org/10.14569/ijacsa.2024.0150721

Pang, D., Guan, Z., Luo, T., Su, W., & Dou, R. (2023). Real-time detection of road manhole covers with a deep learning model. Scientific Reports, 13(1). https://doi.org/10.1038/s41598-023-43173-z

Russell, S. J., & Norvig, P. (2010). Artificial intelligence : a modern approach. Pearson, Cop.

Su, Y., Wang, J., Li, D., Wang, X., Hu, L., Yao, Y., & Kang, Y. (2023). End-to-end deep learning model for underground utilities localization using GPR. Automation in Construction, 149, 104776. https://doi.org/10.1016/j.autcon.2023.104776

Suleimenov, I. E., Vitulyova, Y. S., Bakirov, A. S., & Gabrielyan, O. A. (2020). Artificial Intelligence. Proceedings of the 2020 6th International Conference on Computer and Technology Applications. https://doi.org/10.1145/3397125.3397141

Tian, C., Kang, K., Zheng, Y., Song, K., & Debs, L. (2023). Feasibility of low-cost 3D reconstruction of small infrastructure assets: a case study of fire hydrants. Computing in Civil Engineering, 352–360. https://doi.org/10.1061/9780784485224.043

Timofte, R., & Gool, L. V. (2011). Multi-view manhole detection, recognition, and 3D localisation. IEEE International Conference on Computer Vision Workshops . https://doi.org/10.1109/iccvw.2011.6130242

Vishnani, V., Adhya, A., Bajpai, C., Chimurkar, P., & Khandagle, K. (2020). Manhole detection using image processing on Google Street View imagery. In 2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT), 684–688. https://doi.org/10.1109/icssit48917.2020.9214219

Wang, D., & Huang, Y. (2024). Manhole cover classification based on super-resolution reconstruction of unmanned aerial vehicle aerial imagery. Applied Sciences, 14(7), 2769–2769. https://doi.org/10.3390/app14072769

Wei, Z., Yang, M., Wang, L., Ma, H., Chen, X., & Zhong, R. (2019). Customized mobile LiDAR system for manhole cover detection and identification. *Sensors*, *19*(10), 2422–2422. https://doi.org/10.3390/s19102422

Yamaguchi, T., Mizutani, T., & Nagayama, T. (2021). Mapping subsurface utility pipes by 3-D Convolutional Neural Network and Kirchhoff Migration using GPR images. IEEE Transactions on Geoscience and Remote Sensing, 59(8), 6525–6536. https://doi.org/10.1109/tgrs.2020.3030079

Yu, Y., Guan, H., & Zheng, J. (2015). Automated detection of urban road manhole covers using mobile laser scanning data. *IEEE Transactions on Intelligent Transportation Systems*, *16*(6), 3258–3269. https://doi.org/10.1109/tits.2015.2413812

Zhang, Y., Lu, X., Li, W., Yan, K., Mo, Z., Lan, Y., & Wang, L. (2023). Detection of power poles in orchards based on improved Yolov5s model. Agronomy, 13(7), 1705–1705. https://doi.org/10.3390/agronomy13071705

Zhou, B., Zhao, W., Guo, W., Li, L., Zhang, D., Mao, Q., & Li, Q. (2022). Smartphone-based road manhole cover detection and classification. Automation in Construction, 140, 104344. https://doi.org/10.1016/j.autcon.2022.104344